NLP-Analysis_of_Automotive_Discussion_Forum

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This notebook shows the analysis conducted on around 10,000 comments posted on Edmunds Mid-Size Sedan forum to determine top 10 brands by frequency and the most frequently mentioned attributes for these cars. Furthermore, analysis is done to see which attributes are associated with the top 5 brand names in the forum. Additional analysis is conducted to determine the most aspirational brand. The report also outlines the business insights derived from these results and how the companies can leverage this analysis to determine areas of improvement for business growth.

Forum Link: https://forums.edmunds.com/discussion/7526/general/x/midsize-sedans-2-0

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np

import nltk
#nltk.download()
from nltk.tokenize import sent_tokenize, word_tokenize
import string

import matplotlib.pyplot as plt
from sklearn.manifold import MDS
from sklearn.metrics import euclidean_distances
from sklearn import manifold

import warnings
warnings.filterwarnings('ignore')
```

Loading data

In [2]:
```
df=pd.read_csv(r"C:\Users\vivek\Desktop\edmunds_extraction (2).csv")
models=pd.read_csv(r"C:\Users\vivek\Desktop\models_sanitized.csv", header = None)
models=models.rename(columns={0:'Brand', 1:'Model'})
```

Data cleaning

Lowercasing brands and models database

In [3]:
```
for i in range(len(models)):
    models['Brand'][i]=models['Brand'][i].lower()
    models['Model'][i]=models['Model'][i].lower()

models=models.drop_duplicates()
```

First we tokenize the comments into a string list

In [4]:
```
word_comments=[]

# Tokenize
for i in range(len(df)):
    word_comments.append(word_tokenize(df['Comment'][i].lower()))
df['comment_clean']=word_comments
```

Then, we will filter away from the comments words that are not neccesary or punctuations.

In [5]:
```
stopwords = set(nltk.corpus.stopwords.words('english'))
punctuation = set(string.punctuation)

# Filter words in stopwords
word_comments_filt=[]
for i in range(len(df)):
    filt=[]
    for word in df['comment_clean'][i]:
        if word not in stopwords:
            filt.append(word)
    word_comments_filt.append(filt)
df['comment_clean']=word_comments_filt

# Filter punctuation words
word_comments_filt=[]
for i in range(len(df)):
    filt=[]
    for word in df['comment_clean'][i]:
        if word not in punctuation:
            filt.append(word)
    word_comments_filt.append(filt)
df['comment_clean']=word_comments_filt
```

Calculating word frequency

In [6]:
```
word_comments=[]

for i in range(len(df)):
    word_comments.append(nltk.FreqDist(df['comment_clean'][i]))

df['comment_wordcount']=word_comments
df
```

Out[6]:

	Counter	Date	User	Comment	comment_clean	comment_wordcount
0	1	2007-04-11 18:52:00	motownusa	Hi Pat:You forgot the Chrysler Sebring	[hi, pat, forgot, chrysler, sebring]	{'hi': 1, 'pat': 1, 'forgot': 1, 'chrysler': 1...
1	2	2007-04-11 19:33:00	exshoman	I'm sure some folks would appreciate having th...	['m, sure, folks, would, appreciate, malibu, i...	{"m': 1, 'sure': 1, 'folks': 1, 'would': 1, '...
2	3	2007-04-12 06:51:00	targettuning	You can try to revive this topic but without b...	[try, revive, topic, without, able, discuss, h...	{'try': 1, 'revive': 1, 'topic': 1, 'without':...
3	4	2007-04-12 08:43:00	pat	Model vs. model is exactly what we're here for...	[model, vs., model, exactly, 're, manufacturer...	{'model': 2, 'vs.': 2, 'exactly': 1, "re': 1,...
4	5	2007-04-13 11:49:00	perna	The Altima is my favorite of the bunch. It is ...	[altima, favorite, bunch, amongst, fastest, be...	{'altima': 2, 'favorite': 1, 'bunch': 2, 'amon...
...	...	...	...	...	...	...
9988	9996	2008-07-24 09:06:00	igozoomzoom	It's quite possible that the 2010 Fusion/Milan...	['s, quite, possible, 2010, fusion/milan, new,...	{"s': 5, 'quite': 1, 'possible': 1, '2010': 2...
9989	9997	2008-07-24 09:07:00	moocow1	Of course plans don't mean reality. I expect a...	[course, plans, n't, mean, reality, expect, le...	{'course': 2, 'plans': 2, 'n't': 1, 'mean': 1,...
9990	9998	2008-07-24 09:27:00	akirby	These aren't "plans" - the cars hit the factor...	[n't, ``, plans, '', cars, hit, factory, floor...	{'n't': 1, '``': 2, 'plans': 1, "''": 2, 'cars...
9991	9999	2008-07-24 09:33:00	thegraduate	In my head, a nameplate's sales are a nameplat...	[head, nameplate, 's, sales, nameplate, 's, sa...	{'head': 1, 'nameplate': 2, "s': 2, 'sales': ...
9992	10000	2008-07-24 09:37:00	thegraduate	22/33 for the 2009 Malibu is on its way (See I...	[22/33, 2009, malibu, way, see, 'm, sure, chan...	{'22/33': 1, '2009': 3, 'malibu': 2, 'way': 1,...

9993 rows × 6 columns

Task A

Identify top 10 brands by frequency

In [7]:
```
df_a=df.copy()
```

Create a count column per brand, it will initially be empty

In [8]:
```
brands=models['Brand'].unique()

for brand in brands:
    df_a[brand]=0
```

Define how many times the brand is mentioned in the comment

In [9]:
```
for i in range(len(df_a)):
    for word in df_a['comment_wordcount'][i]:
        if word in brands:
            df_a[word][i]=df_a['comment_wordcount'][i][word]
```

Create a dictionary of models per brand and add their mentions to their respective brands

In [10]:
```
model_brands={}
for model in models['Model'].tolist():
    model_brands[model]=models[models['Model']==model]['Brand'].to_list()[0]

for i in range(len(df_a)):
    for word in df_a['comment_wordcount'][i]:
        if word in models['Model'].tolist():
            df_a[model_brands[word]][i]=df_a[model_brands[word]][i]+df_a['comment_wordcount'][i][word]
```

In [11]:
```
df_a[brands]
```

Out[11]:

	acura	audi	bmw	buick	cadillac	chevrolet	chrysler	dodge	ford	honda	...	mercury	mitsubishi	nissan	pontiac	saturn	sub
0	0	0	0	0	0	0	2	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	2	3	...	0	0	3	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
9988	0	0	0	0	0	2	0	0	3	4	...	0	0	0	0	0	
9989	0	0	0	0	0	0	0	0	2	1	...	0	0	0	0	0	
9990	0	0	0	0	0	0	0	0	2	0	...	0	0	0	0	0	
9991	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0	0	
9992	0	0	0	0	0	2	0	0	0	0	...	0	0	0	0	0	

9993 rows × 26 columns

Finally, we adjust the brands mentions to only count one per comment

In [12]:
```
for brand in brands:
    for i in range(len(df_a)):
        if df_a[brand][i]>0:
            df_a[brand][i]=1
df_a[brands]
```

Out[12]:

	acura	audi	bmw	buick	cadillac	chevrolet	chrysler	dodge	ford	honda	...	mercury	mitsubishi	nissan	pontiac	saturn	sub
0	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	1	1	...	0	0	1	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
9988	0	0	0	0	0	1	0	0	1	1	...	0	0	0	0	0	
9989	0	0	0	0	0	0	0	0	1	1	...	0	0	0	0	0	
9990	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	
9991	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0	0	
9992	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	

9993 rows × 26 columns

Top ten brands

In [13]:
```
top10brands={}

for brand in brands :
    top10brands[brand]=df_a[brand].sum()

top10brands=pd.DataFrame.from_dict(top10brands, orient='index',columns=['Count'])
top_brands=(top10brands.sort_values(by=['Count'], ascending=False).head(10)).index.to_list()

print('The following brands are the TOP10 most mentioned in the forum:')
display(top10brands.sort_values(by=['Count'], ascending=False).head(10))
```

```
The following brands are the TOP10 most mentioned in the forum:
```

	Count
honda	3893
ford	2148
toyota	2010
hyundai	1352
mazda	1232
nissan	998
chevrolet	746
chrysler	514
saturn	491
subaru	291

Calculate lift ratios

First we define a function to calculate lift. This is an function that iterates around the brand mentions

In [14]:
```
def calculate_lift(a, b, data):
    count_a = 0
    count_b = 0
    count_a_b = 0
    n = len(data)

    if a==b:
        return float(1)

    for i in range(n):
        if data[a][i]==1:
            count_a += 1
        if data[b][i]==1:
            count_b += 1
        if data[a][i]==1 and data[b][i]==1:
            count_a_b += 1
    if count_a == 0:
        return (float(n)*count_a_b)/(count_b)
    elif count_b == 0:
        return (float(n)*count_a_b)/(count_a)
    else:
        return (float(n)*count_a_b)/(count_a*count_b)
```

Calculate lift for top 10 brands

In [15]:
```
lift={}

for brand_a in top_brands:
    for brand_b in top_brands:
        lift[brand_a,brand_b]=calculate_lift(brand_a,brand_b,df_a)
```

Create lift matrix

In [16]:
```
lift_matrix=pd.DataFrame(index=top_brands, columns=top_brands)

for a in top_brands:
    for b in top_brands:
        lift_matrix[b][a]=lift[a,b]

lift_matrix
```

Out[16]:

	honda	ford	toyota	hyundai	mazda	nissan	chevrolet	chrysler	saturn	subaru
honda	1.0	1.187855	1.734264	1.420157	1.131359	1.592105	1.496794	1.433277	1.495189	1.561319
ford	1.187855	1.0	1.481309	1.156177	1.302777	1.337867	1.396918	1.411962	1.459153	1.071133
toyota	1.734264	1.481309	1.0	1.798175	1.101671	2.396152	2.185923	1.479886	2.055485	1.264266
hyundai	1.420157	1.156177	1.798175	1.0	1.079894	1.91077	1.783417	1.624929	1.505351	1.549373
mazda	1.131359	1.302777	1.101671	1.079894	1.0	1.536089	0.945944	0.804808	1.040745	2.703734
nissan	1.592105	1.337867	2.396152	1.91077	1.536089	1.0	2.2281	1.32468	2.793859	2.202178
chevrolet	1.496794	1.396918	2.185923	1.783417	0.945944	2.2281	1.0	1.667915	4.938035	1.703201
chrysler	1.433277	1.411962	1.479886	1.624929	0.804808	1.32468	1.667915	1.0	1.306668	1.336195
saturn	1.495189	1.459153	2.055485	1.505351	1.040745	2.793859	4.938035	1.306668	1.0	1.888362
subaru	1.561319	1.071133	1.264266	1.549373	2.703734	2.202178	1.703201	1.336195	1.888362	1.0

Plot MDS

Calculate dissimilarity matrix

In [17]:
```
dissimilarity_matrix = 1/lift_matrix
```

Plot MDS

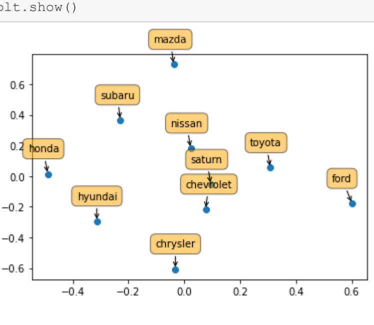
In [18]:
```
import matplotlib.pyplot as plt
from sklearn.manifold import MDS
from sklearn.metrics import euclidean_distances
from sklearn import manifold

seed = np.random.RandomState(seed=3)
mds = manifold.MDS(n_components=2, max_iter=3000, eps=1e-9,
      random_state=seed, dissimilarity="precomputed", n_jobs=1)
results = mds.fit(dissimilarity_matrix)
coords = results.embedding_

plt.subplots_adjust(bottom = 0.1)
plt.scatter(
    coords[:, 0], coords[:, 1], marker = 'o'
    )
for label, x, y in zip(lift_matrix, coords[:, 0], coords[:, 1]):

    plt.annotate(
        label,
        xy = (x, y), xytext = (-20, 20),
        textcoords = 'offset points',ha = 'left', va = 'bottom',
        bbox = dict(boxstyle = 'round,pad=0.5', fc = 'orange', alpha = 0.5),
        arrowprops = dict(arrowstyle = '->', connectionstyle = 'arc3,rad=0'))

plt.show()
```



Task B

What insights can you offer brand managers from your analysis in Task A? Choose two brands that you can offer the most interesting/useful insights for.

In this dataset we chose, the main target behind peoples posts is to discuss mid-sized sedans. The distance between the car brands measures the dissimilarity between them, and the closer brands are, meaning that people associate them to each other.

As we can see, Mazda is quite far away meaning that people don't associate it to other car brands. As a brand manager, you would want to focus on Mazda so to raise its competitiveness versus other cars. When compared to Subaru, Mazda provides above its weight, a classy interior, much improved driving manners, and perhaps above all, optional all-wheel drive, which is something Subaru lacks. Also, when compared compared to Nissan, Mazda is has very similar characteristics but is less expensive. This can be used to attract Nissan users towards a more economy friendly car. An interest additional insight is that Mazda can try to attract Saturn previous users, which stopped production in 2009 and made very similar cars to Mazda.

Now another brand to focus on can be Chevrolet. Chevrolet competes closely with Saturn, and both are American brands. However, as mentioned earlier, Saturn stopped manufacturing so Chevrolet can try attract Saturn's previous user as the transition will be very smooth. Chevrolet also competes closely with Japanese manufactured cars such as Nissan and Toyota, have very similar specs. This can also be used by customers of these brands based in the US, to support a local manufacturing company.

Task C

Identifying the top 5 attributes and determining which brands among the top 5 they are mostly associated with

First substituting models as brands and making sure each word is counted once per post

In [19]:
```
df_a["comments_unique"] = df_a["comment_clean"].apply(lambda list_of_words: [x if x not in model_brands
 else model_brands[x] for x in list_of_words])
df_a["comments_unique"] = df_a["comments_unique"].apply(lambda x: sorted(set(x)))
df_a
```

Out[19]:

	Counter	Date	User	Comment	comment_clean	comment_wordcount	acura	audi	bmw	buick	...	mitsubishi	nis
0	1	2007-04-11 18:52:00	motownusa	Hi Pat:You forgot the Chrysler Sebring	[hi, pat, forgot, chrysler, sebring]	{'hi': 1, 'pat': 1, 'forgot': 1, 'chrysler': 1...	0	0	0	0	...	0	
1	2	2007-04-11 19:33:00	exshoman	I'm sure some folks would appreciate having th...	['m, sure, folks, would, appreciate, malibu, i...	{"m': 1, 'sure': 1, 'folks': 1, 'would': 1, '...	0	0	0	0	...	0	
2	3	2007-04-12 06:51:00	targettuning	You can try to revive this topic but without b...	[try, revive, topic, without, able, discuss, h...	{'try': 1, 'revive': 1, 'topic': 1, 'without':...	0	0	0	0	...	0	
3	4	2007-04-12 08:43:00	pat	Model vs. model is exactly what we're here for...	[model, vs., model, exactly, 're, manufacturer...	{'model': 2, 'vs.': 2, 'exactly': 1, "re': 1,...	0	0	0	0	...	0	
4	5	2007-04-13 11:49:00	perna	The Altima is my favorite of the bunch. It is ...	[altima, favorite, bunch, amongst, fastest, be...	{'altima': 2, 'favorite': 1, 'bunch': 2, 'amon...	0	0	0	0	...	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
9988	9996	2008-07-24 09:06:00	igozoomzoom	It's quite possible that the 2010 Fusion/Milan...	['s, quite, possible, 2010, fusion/milan, new,...	{"s': 5, 'quite': 1, 'possible': 1, '2010': 2...	0	0	0	0	...	0	
9989	9997	2008-07-24 09:07:00	moocow1	Of course plans don't mean reality. I expect a...	[course, plans, n't, mean, reality, expect, le...	{'course': 2, 'plans': 2, 'n't': 1, 'mean': 1,...	0	0	0	0	...	0	
9990	9998	2008-07-24 09:27:00	akirby	These aren't "plans" - the cars hit the factor...	[n't, ``, plans, '', cars, hit, factory, floor...	{'n't': 1, '``': 2, 'plans': 1, "''": 2, 'cars...	0	0	0	0	...	0	
9991	9999	2008-07-24 09:33:00	thegraduate	In my head, a nameplate's sales are a nameplat...	[head, nameplate, 's, sales, nameplate, 's, sa...	{'head': 1, 'nameplate': 2, "s': 2, 'sales': ...	0	0	0	0	...	0	
9992	10000	2008-07-24 09:37:00	thegraduate	22/33 for the 2009 Malibu is on its way (See I...	[22/33, 2009, malibu, way, see, 'm, sure, chan...	{'22/33': 1, '2009': 3, 'malibu': 2, 'way': 1,...	0	0	0	0	...	0	

9993 rows × 33 columns

Obtaining a list of possible attributes (by filtering out adjectives and nouns to reduce the computation time). The filtering part is to get a high level overview of the attributes that are mentioned in the comments

In [20]:
```
#Obtain POS for the tokens
df2 = df_a[['Counter', 'Date', 'User', 'Comment','comment_clean', 'comments_unique']]
df2['pos']=df2['comments_unique'].apply(nltk.tag.pos_tag)

# Extract the list of nouns since the attributes will be nouns and adjectives; this will help in reduci
ng the amount of words that needs to be filtered
df2.loc[:,'nouns_adj']=df2['pos'].apply(lambda pos_list: [x[0] for x in pos_list if x[1] == 'NN'or x[1]
 == 'JJR'or x[1]== 'JJS'])
```

Geting the frequencies for the nouns and adjectives

In [21]:
```
#creating list of unique nouns and adjectives
noun_adj_df = df2['nouns_adj'].apply(pd.Series)
noun_adj_list = noun_adj_df.stack().unique()

# get the frequencies for the nouns and adjectives:
noun_adj_df= pd.DataFrame(noun_adj_list)
noun_adj_df.columns=['nouns_adj']

# join the above table with frequency table

## get frequency of all words
all_words = df2['comments_unique'].sum()
freq_dist_words = nltk.FreqDist(all_words)

dfwords_dist=pd.DataFrame(list(freq_dist_words.items()), columns=['word', 'frequency'])
noun_freq_df = pd.merge(noun_adj_df, dfwords_dist, right_on='word', left_on='nouns_adj')
noun_freq_df = noun_freq_df.sort_values(by=['frequency'], ascending = False)
noun_freq_df
```

Out[21]:

	nouns_adj	word	frequency
25	honda	honda	3893
19	car	car	3648
2821	like	like	2726
1653	one	one	2378
108	think	think	2172
...	...	...	...
8383	fury	fury	1
8382	applique	applique	1
4316	snatch	snatch	1
4317	you.dumb	you.dumb	1
9280	tower	tower	1

12332 rows × 3 columns

Some of the attributes that can be clubbed together under synonyms. The approach is to make a csv file of attributes similar to the models ones so that the attributes can be clubbed together and their frequency can be calculated.

In [22]:
```
attr_list = ['engine','year','price', 'power', 'drive','value', "year","mileage"
            ,"quality","reliability","cost" ,"warranty","mpg","speed","hp" ,"control"
            ,"gm","mph","performance","size","auto" ,"design" ,"transmission","brand"
            ,"seat","wheel" ,"room","use" ,"experience" ,"cylinder","midsize","feel" ,"rpm"
            ,"safety","torque","door","maintenance" ,"volume","area","manufacturer","acceleration","st
yle"
            ,"space","motor","stability" ,"range","rating" ,"diesel" ,"oil" ,"body","interior "
            ,"weight","noise","leather","type" ,"cyl","sport","comfort" ,"rate","make","capacity"
            ,"limit","rwd","gear","luxury","pricing","age","navigation","wood","mile"
            ,"average","exhaust","foot","slip","liter","tank","beat","gasoline","color","trim"
            ,"conditions" ,"rpms","gallon","shape","styling","efficiency","legroom","horsepower","dura
bility"
            ,"headroom","audio","aluminium","metal","lbs","steel","apperance","drivetrain","efficient"
,"longetivity","material"
            ,"expense","moonroof", "bigger", "biggest", "smaller", "smallest", "economy", ]
attributes = pd.read_csv(r"C:\Users\vivek\Desktop\attributes.csv")
brand_att={}
for att in attributes['Words'].tolist():
    brand_att[att]=attributes[attributes['Words']==att]['Attribute'].to_list()[0]

print(attributes)
```

```
       Words    Attribute
0     engine  performance
1       year        model
2      price        price
3      power  performance
4      drive        price
..       ...          ...
89   biggest         size
90   smaller         size
91  smallest         size
92     money        price
93   economy  performance

[94 rows x 2 columns]
```

Substituting attributes under their synonyms and that each word is counted once per post

In [23]:
```
df2['comments_attr'] = df2['comments_unique'].apply(lambda list_of_att: [x if x not in brand_att else
brand_att[x] for x in list_of_att])
df2['comments_attr'] = df2['comments_attr'].apply(lambda x: sorted(set(x)))
df2
```

Out[23]:

	Counter	Date	User	Comment	comment_clean	comments_unique	pos	nouns_adj	comments_attr
0	1	2007-04-11 18:52:00	motownusa	Hi Pat:You forgot the Chrysler Sebring	[hi, pat, forgot, chrysler, sebring]	[chrysler, forgot, hi, pat]	[(chrysler, NN), (forgot, VBD), (hi, JJ), (pat...	[chrysler, pat]	[chrysler, forgot, hi, pat]
1	2	2007-04-11 19:33:00	exshoman	I'm sure some folks would appreciate having th...	['m, sure, folks, would, appreciate, malibu, i...	['m, appreciate, chevrolet, folks, included, s...	[('m, VBP), (appreciate, JJ), (chevrolet, NN),...	[chevrolet]	['m, appreciate, chevrolet, folks, included, s...
2	3	2007-04-12 06:51:00	targettuning	You can try to revive this topic but without b...	[try, revive, topic, without, able, discuss, h...	[able, agree, comparisons, discuss, discussion...	[(able, JJ), (agree, JJ), (comparisons, NNS), ...	[discussion, gets..or, manufacturer, spite, ta...	[able, agree, comparisons, discuss, discussion...
3	4	2007-04-12 08:43:00	pat	Model vs. model is exactly what we're here for...	[model, vs., model, exactly, 're, manufacturer...	['re, 's, 've, already, around, auto, avoid, b...	[('re, VBP), ('s, POS), ('ve, VBP), (already, ...	[auto, discussion, exclusion, manufacturer, ne...	['re, 's, 've, already, around, auto, avoid, b...
4	5	2007-04-13 11:49:00	perna	The Altima is my favorite of the bunch. It is ...	[altima, favorite, bunch, amongst, fastest, be...	['ll, 's, 've, 2002, 2007, 2007., advice, also...	[('ll, MD), ('s, POS), ('ve, VBP), (2002, CD),...	[advice, best, bunch, car, choice, comment, fa...	['ll, 's, 've, 2002, 2007, 2007., advice, also...
...	...	...	...	...	...	...	...	...	...
9988	9996	2008-07-24 09:06:00	igozoomzoom	It's quite possible that the 2010 Fusion/Milan...	['s, quite, possible, 2010, fusion/milan, new,...	['', '09, 'm, 's, ..., .the, 2.5l, 200, 2010, ...	[('', ''), ('09, VBZ), ('m, VBP), ('s, POS), (...	[balance, beat, better, camcord, case, chevrol...	['', '09, 'm, 's, ..., .the, 2.5l, 200, 2010, ...
9989	9997	2008-07-24 09:07:00	moocow1	Of course plans don't mean reality. I expect a...	[course, plans, n't, mean, reality, expect, le...	['m, 're, 1mpg, 20-22, 23/33, 25/35, 30-32, 6,...	[('m, VBP), ('re, VBP), (1mpg, CD), (20-22, JJ...	[advantage, best, course, economy, fuel, highw...	['m, 're, 1mpg, 20-22, 23/33, 25/35, 30-32, 6,...
9990	9998	2008-07-24 09:27:00	akirby	These aren't "plans" - the cars hit the factor...	[n't, ``, plans, '', cars, hit, factory, floor...	['', 'll, 's, 4, 6, ``, achieve, advantage, an...	[('', ''), ('ll, MD), ('s, POS), (4, CD), (6, ...	[advantage, anything, better, class, company, ...	['', 'll, 's, 4, 6, ``, achieve, advantage, an...
9991	9999	2008-07-24 09:33:00	thegraduate	In my head, a nameplate's sales are a nameplat...	[head, nameplate, 's, sales, nameplate, 's, sa...	['s, calls, choice, different, everyone, head,...	[('s, POS), (calls, NNS), (choice, NN), (diffe...	[choice, everyone, head, honda, hyundai, intend]	['s, calls, choice, different, everyone, head,...
9992	10000	2008-07-24 09:37:00	thegraduate	22/33 for the 2009 Malibu is on its way (See I...	[22/33, 2009, malibu, way, see, 'm, sure, chan...	['d, 'm, 1, 2.4l, 2008, 2009, 22/32, 22/33, 6-...	[('d, MD), ('m, VBP), (1, CD), (2.4l, CD), (20...	[chevrolet, get, mileage, model, mpg, way]	['d, 'm, 1, 2.4l, 2008, 2009, 22/32, 22/33, 6-...

9993 rows × 9 columns

Top 5 attributes based on their frequency

In [24]:
```
all_attributes = attributes['Attribute'].unique()
def calc_frequency(comments,word_list):
    freq_word=0
    for i in comments:
        if word_list in i:
            freq_word += 1
    return freq_word

# Calculate freq for attr
df_top_attribute = pd.DataFrame(columns=['attribute','frequency'])
for i,attribute in enumerate(all_attributes):
        temp_frequency =calc_frequency( df2.comments_attr,str(attribute))
        df_top_attribute.loc[i]=[str(attribute),temp_frequency]

df_top5_attribute = df_top_attribute.sort_values(by='frequency',ascending=False).head(7)
df_top5_attribute.drop([1,10])
```

Out[24]:

	attribute	frequency
0	performance	2649
2	price	2064
11	interior	1373
7	size	1211
8	transmission	841

In [25]:
```
top5_attr = ['performance', 'price', 'interior','size','transmission']
```

Lift ratio between brands and attributes

Calculating Lift between brands and attributes and generating lift matrix

In [26]:
```
##calculating lift
def calc_lift(a, b,comments):
    num_a = 0
    num_b = 0
    num_a_b = 0
    n = len(comments)
    if a==b:
        return 1
    for i in comments:
        if a in i:
            num_a += 1
        if b in i:
            num_b += 1
        if a in i and b in i:
            num_a_b += 1
    if num_a == 0:
        return (float(n)*num_a_b)/(num_b)
    elif num_b == 0:
        return (float(n)*num_a_b)/(num_a)
    else:
        return (float(n)*num_a_b)/(num_a*num_b)

# Grouped Brands and attribute lifts
top_5brands = (top10brands.sort_values(by=['Count'], ascending=False).head(5)).index.to_list()
df_lift_brand_attr=pd.DataFrame(columns=['brand','attribute','lift'])
i=0
for brand in top_5brands:
    for attr in top5_attr:
        temp_lift=calc_lift(str(brand), str(attr),df2.comments_attr)
        df_lift_brand_attr.loc[i]=[ str(brand),str(attr),temp_lift]
        i=i+1

df3 = df_lift_brand_attr.sort_values('lift',ascending = False).groupby('brand').head(10)

lift_matrix_attr_brand = df3.pivot(index='brand', columns='attribute')
print(lift_matrix_attr_brand)
```

```
               lift
attribute  interior performance     price      size transmission
brand
ford       1.067337    1.331217  1.113471  1.102553     1.183803
honda      1.336740    1.203514  1.294650  1.388381     1.373498
hyundai    1.588074    1.040749  1.561335  1.391586     0.790980
mazda      1.518266    1.417700  1.402955  1.681182     1.755337
toyota     1.314425    1.197398  1.387435  1.395837     0.963588
```

Task D:

What advice will you give to a (i) product manager, and (ii) marketing/advertising manager of these brands based on your analysis in Task C? For this assignment, you can assume the sentiment (e.g., that it is positive)

ASSUMPTIONS:
• The sentiment is positive
• Similar attributes were clubbed together based on personal understanding, thus, the interpretation of analysis results might be subjective
NOTE:
• The following perceptions are with respect to other brands in Top 5
• The result are aimed at 'Mid-Size' sedans (primarily in the American Market) in the years 2007 and 2008
• Results were matched with Actual Data (News/Press Articles for the time period: Jan 1, 2007 to Jan 1, 2009 and location: USA – via VPN)

****

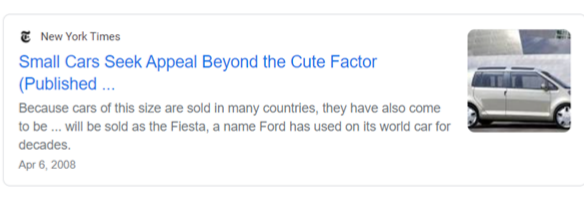
Ford:

The brand is perceived positively with Performance
The brand is not perceived positively with Interior, Price, and Size

A. Product Manager: Although our products are great in terms of performance, they are not perceived well in-terms of Size, Interior and Price. We need to invest in our R&D to make cars which have a more appealing interior, are priced reasonably and most importantly, are appropriately-sized i.e. neither too sleek, nor too bulky.

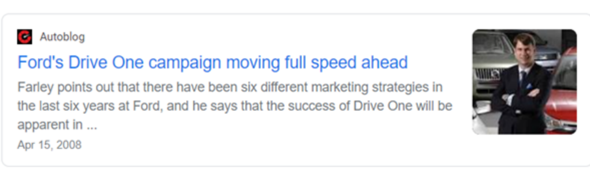
B. Marketing/Advertising Manager: We would need to do a complete revamp of advertising and marketing to get rid of the tarnished brand image. This can be done through launch of better products and a massive marketing campaign which compels people to try out the new, better products.

Matching Results with Data from the period 2007-08, which resonate with our recommendations:


New York Times
Small Cars Seek Appeal Beyond the Cute Factor (Published ...
Because cars of this size are sold in many countries, they have also come to be ... will be sold as the Fiesta, a name Ford has used on its world car for decades.
Apr 6, 2008

At the New York show, Ford displayed a design study called the Verve, a version of a new small car that will be sold as the Fiesta, a name Ford has used on its world car for decades. European sales start this fall with an American introduction in 2010.

***Ref: https://www.nytimes.com/2008/04/06/automobiles/06SMALL.html**


Autoblog
Ford's Drive One campaign moving full speed ahead
Farley points out that there have been six different marketing strategies in the last six years at Ford, and he says that the success of Drive One will be apparent in ...
Apr 15, 2008

***Ref: https://www.autoblog.com/2008/04/15/fords-drive-one-campaign-moving-full-speed-ahead/**

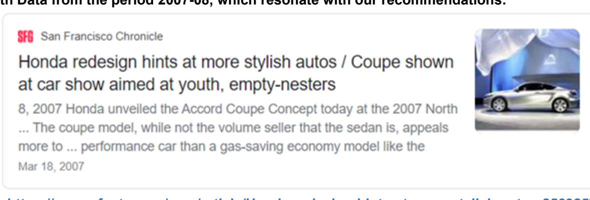
Honda:

The brand is perceived positively with Okay with interior, Okay with performance, Okay with Price, Okay with Size, Okay with Transmission.

A. Product Manager: Our brand and products are among the popular ones, and our products demonstrate a balanced mix of attributes, making our products the definition of "daily commuter" and popular, "mass-production" cars. Thus, we need better products which focus more on certain attributes and cater to certain audience.

B. Marketing/Advertising Manager: Although being balanced out in the attributes boosts sales, this might also harm the company's image in the long-term as being "average". Thus, we need products which can help break this brand image by launching a few products which also cater towards a certain cluster of customers (e.g. Performance-oriented cars for younger population).

Matching Results with Data from the period 2007-08, which resonate with our recommendations:


San Francisco Chronicle
Honda redesign hints at more stylish autos / Coupe shown at car show aimed at youth, empty-nesters
8, 2007 Honda unveiled the Accord Coupe Concept today at the 2007 North ... The coupe model, while not the volume seller that the sedan is, appeals more to ... performance car than a gas-saving economy model like the
Mar 18, 2007

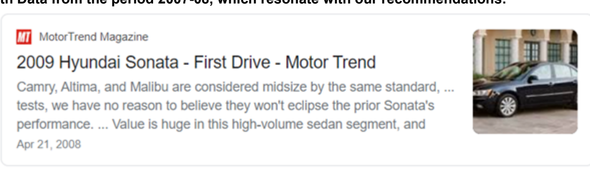
***Ref: https://www.sfgate.com/cars/article/Honda-redesign-hints-at-more-stylish-autos-2569257.php**

Hyundai:

The brand is perceived positively with Interior and Price.
The brand is not perceived positively with Performance and Transmission. (as compared to other companies in Top 5)
Hyundai has a lift ratio of 0.790980 with Transmission. Typically, a lift ratio of less than 1 proposes that the two terms show up together not exactly (more than) one would expect by the simple event of every one of the two terms in the discussion independently. Thus, we cannot make any concrete comments about Hyundai's transmission.

A. Product Manager: Our products are well received by the customers as reasonably-priced and people tend to like our interiors better than the competitors. However, the products are not well-perceived in terms of performance. Thus, we should fix this issue and deliver a better product, which is more performance-oriented.
B. Marketing/Advertising Manager: Since, our brand is perceived as an affordable one we can leverage this brand image and overcome our shortcomings by launching new products which lie at the intersection of performance and "value-for-money" domains.

Matching Results with Data from the period 2007-08, which resonate with our recommendations:



***Ref: https://www.autoblog.com/2008/02/06/chicago-2008-hyundai-officially-releases-the-2009-sonata/**

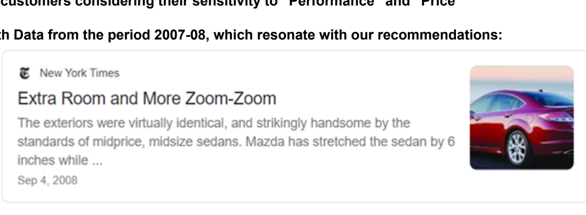
Mazda:

The brand is perceived positively with Interior, Performance, Price, Size and Transmission.

A. Product Manager: Our products are perceived as reasonably-priced, high-performance cars with a wide range of transmissions available. Thus, the products should be aimed to maintain and further bolster this perception.

B. Marketing/Advertising Manager: Since, the products produced are top-notch and better than the competition, special attention must be paid to market the products against already existing market leaders. This can be done by becoming the consistent market leader in certain attributes, such as "Performance" and "Price". Target marketing on younger population which are more likely to be potential customers considering their sensitivity to "Performance" and "Price"

Matching Results with Data from the period 2007-08, which resonate with our recommendations:



Ref: https://www.nytimes.com/2008/09/07/automobiles/autoreviews/07AUTO.html

Toyota:

The brand is perceived positively with Size.
The brand is NOT perceived positively with performance and transmission. (as compared to other companies in Top 5)
Toyota has a lift ratio of 0.963588 with Transmission. Typically, a lift ratio of less than 1 proposes that the two terms show up together not exactly (more than) one would expect by the simple event of every one of the two terms in the discussion independently. Thus, we cannot make any concrete comments about Hyundai's transmission.

A. Product Manager: Our cars are perceived to be appropriately-sized since they are designed with an intention of being a "family-car". Thus, our products have enough boot space and leg room which contribute to the perception. This also leads to a perception that it has lower performance as compared to other brands, which focus more on "performance". Thus, we should focus on building a product which is a sportier-version of the same product.

B. Marketing/Advertising Manager: Since, our products are perceived in positive light in most attributes, we would need to run massive ad-campaigns to make the customers aware of our product's capabilities.

Task E:

Which is the most aspirational brand in your data in terms of people actually wanting to buy or own? Describe your analysis. What are the business implications for this brand?

The approach that we followed to determine the aspirational brand was to create a list of aspirational words. Some of these words included wish, hope, want, etc. Then lift ratios between these words and all the brands were generated to see if a particular word was primarily associated with any brand. To find the most aspirational brand, all the words in the list were substituted as 'aspiration' in the comments.Then the lift ratios between the term 'aspiration' and all the brands were generated.

As it can be seen below, Volvo had the highest lift ratio with the aspirational words followed by Audi and Mercedes. If we analyze the lift ratios of Volvo with aspirational words, it was mostly associated with: afford, fancy, choice, like, hope, need, prefer, and want. In fact, Volvo and the word 'fancy' had the highest lift ratio of 10.23, which further demonstrates Volvo is the brand that people want to own or buy.

This analysis can be extremely helpful for Volvo as it can be seen that people aspire to own a vehicle from their brand. However, this might just be an aspiration due to superior brand image, without any intent to buy the actual product due to other factors such as budget constraints, maintenance and insurance charges, taxes etc. Thus, an additional analysis needs to be performed to determine the potential market and forecast expected revenue to check feasibility of launching a lower-specification product which caters to these potential customers without compromising the company standards and brand image. Furthermore, we would need detailed analysis from more such forums to have a clear understanding of the factors that are significantly responsible for brand aspiration.

Lift ratios for each aspirational word and brand

In [27]:
```
asp = ["hope","choice", "prefer","want","dream","wish","desire","aspire","lean","incline","fancy","cra
ve","need","eager","like","fond","afford","love"]
df_lift_brand_asp=pd.DataFrame(columns=['brand','aspiration','lift'])

i=0
for brand in brands:
    for aspire in asp:
        asp_lift = calc_lift(str(brand), str(aspire), df2.comments_unique)
        df_lift_brand_asp.loc[i]=[str(brand),str(aspire),asp_lift]
        i=i+1

df6 = df_lift_brand_asp.sort_values('lift',ascending = False).groupby('brand').head(10)
lift_matrix_asp_brand = df6.pivot(index='brand', columns='aspiration')
print(lift_matrix_asp_brand)
```

```
                lift                                                       \
aspiration    afford aspire    choice     crave    desire     dream     eager
brand
acura       0.000000    NaN  2.543611       NaN       NaN  0.000000       NaN
audi             NaN    0.0  2.316814       NaN       NaN       NaN       NaN
bmw         4.276361    NaN  1.847067       NaN  2.185696  4.917815  6.557087
buick       3.316628    NaN  2.148801       NaN       NaN       NaN       NaN
cadillac    4.937253    NaN       NaN       NaN       NaN       NaN       NaN
chevrolet   2.329642    NaN  1.383567       NaN  1.488382       NaN       NaN
chrysler    1.690577    NaN  1.004028       NaN  1.080091       NaN       NaN
dodge       2.251183    NaN  1.701598       NaN       NaN       NaN       NaN
ford        1.213626    NaN  1.485220  4.652235  1.292287  1.453823  2.326117
honda       1.450865    NaN  1.434098  2.566915       NaN       NaN  1.711277
hyundai          NaN    NaN  1.596237       NaN  1.231879  1.385864       NaN
infiniti         NaN    0.0  3.518662       NaN       NaN       NaN       NaN
kia         1.519155    NaN  1.312321       NaN       NaN       NaN       NaN
lincoln     2.649258    NaN  1.716420       NaN  6.770325       NaN       NaN
mazda            NaN    NaN  1.789796       NaN  2.703734  2.027800  4.055601
mercedes    7.622426    NaN  1.646158       NaN  9.739766       NaN       NaN
mercury     0.000000    NaN  2.777891       NaN       NaN       NaN       NaN
mitsubishi       NaN    NaN  1.660725       NaN  0.000000  5.527102       NaN
nissan      2.176745    NaN  1.833371       NaN       NaN  2.503257  5.006513
pontiac     1.540703    NaN  0.665468       NaN  3.937352       NaN       NaN
saturn      1.327327    NaN  1.719916       NaN       NaN       NaN       NaN
subaru      1.493052    NaN  2.740768       NaN  3.815578       NaN       NaN
suzuki           NaN    0.0  2.345775  0.000000  0.000000  0.000000       NaN
toyota      1.729267    NaN  1.540509       NaN       NaN  1.242910  2.485821
volkswagen  3.851758    NaN  2.495505       NaN       NaN       NaN  5.906028
volvo       3.561297    NaN  1.538213       NaN       NaN       NaN       NaN

                                                                        \
aspiration      fancy       fond      hope   incline      lean      like
brand
acura             NaN        NaN  2.183376       NaN       NaN  1.656240
audi              NaN        NaN  1.917674       NaN  0.000000  1.855534
bmw          2.458907        NaN       NaN       NaN       NaN       NaN
buick             NaN        NaN  2.371475       NaN  5.085496  1.623031
cadillac     0.000000  28.389205  1.176755  0.000000  0.000000  1.499650
chevrolet    3.348861   1.674430       NaN  1.913635  1.786059  1.370994
chrysler     3.645306        NaN  1.208806       NaN       NaN  1.205296
dodge        3.236075        NaN  2.414481       NaN       NaN  1.101643
ford              NaN   1.744588  1.277557       NaN       NaN       NaN
honda        1.283457        NaN       NaN  1.833511  1.711277  1.275924
hyundai      1.847818        NaN       NaN  2.111792  2.710133  1.393659
infiniti          NaN        NaN  1.294430  0.000000  0.000000  1.466324
kia          2.183785        NaN  0.362078       NaN       NaN  1.409927
lincoln           NaN        NaN  2.525717       NaN       NaN  0.983510
mazda             NaN   4.055601  1.765132       NaN  3.244481       NaN
mercedes    10.957237        NaN  2.725116       NaN       NaN  1.736437
mercury           NaN        NaN  2.043837       NaN  4.382895  1.664085
mitsubishi        NaN        NaN  0.916411       NaN       NaN  1.524718
nissan            NaN        NaN  1.297024  2.860865  1.668838  1.469263
pontiac           NaN        NaN  1.101643       NaN       NaN  1.429926
saturn            NaN   2.544043  2.003598       NaN       NaN  1.493202
subaru            NaN   8.585052  1.957214       NaN  6.868041  1.763620
suzuki            NaN        NaN  2.588860       NaN       NaN  1.283034
toyota       1.864366   1.242910  1.210711       NaN  1.988657  1.254765
volkswagen   4.429521   4.429521  1.285250       NaN       NaN  1.520921
volvo       10.238730        NaN  1.697613       NaN       NaN  1.802858


aspiration      love      need    prefer      want      wish
brand
acura       0.272393  1.197135  1.719966  1.254142  1.029039
audi        1.674711  1.752420  2.114921  1.142318  1.054448
bmw              NaN  1.676528  1.798515  1.775878  2.017565
buick       1.035508  2.167115  1.743599  1.324348  1.955960
cadillac         NaN  1.290418  1.297792  0.262863       NaN
chevrolet        NaN       NaN  1.607453  1.379855       NaN
chrysler    1.407539  1.159870  1.444236       NaN  1.329343
dodge       2.108574  1.323849  1.183479  0.719128  0.885080
ford             NaN       NaN  1.329210       NaN  1.709796
honda       1.277650       NaN  1.364132       NaN       NaN
hyundai          NaN       NaN  1.773905  1.154886  1.200292
infiniti         NaN  1.419460  1.427571  1.156597  4.270513
kia         0.948612  1.091892  1.597283  1.011012  2.389098
lincoln     0.551429  0.865525  2.089129  0.705242  2.083177
mazda       1.468091       NaN  1.807639       NaN  1.941142
mercedes         NaN  1.743197  2.003609  1.623294  1.498426
mercury     1.784889  0.653699  5.259474  0.760919  1.123819
mitsubishi  1.600609  1.130544  1.010670  1.330599  3.023372
nissan      1.676389       NaN  2.174257       NaN       NaN
pontiac     0.641379  1.610735  1.619939  1.148394  1.211493
saturn      1.197197  1.387660  2.674879  1.107130  0.869758
subaru      1.709241       NaN  1.962297       NaN  2.054542
suzuki           NaN  2.129190       NaN  1.156597  0.000000
toyota      1.282279       NaN       NaN       NaN       NaN
volkswagen  1.603447  1.258387       NaN  1.353465       NaN
volvo       0.741265  2.559682  3.744450  1.896061  1.400168
```

Lift ratio between the term 'aspirational' and all the brands

In [28]:
```
## Function to replace the aspirational phrases with the word - "aspiration

# Replacing all aspiration words with term 'aspiration'
df7 = df2.copy(deep = True)
for i in range(len(df7)):
    n = len(df7['comments_unique'][i])
    for j in range(n):
        word = df7['comments_unique'][i][j]
        if word in asp:
            df7['comments_unique'][i][j] = 'aspiration'


def calc_lift_asp(a,b, comments):
    num_a = 0
    num_b = 0
    num_a_b = 0
    n = len(comments)
    if a==b:
        return 1
    for i in comments:
        if a in i:
            num_a += 1
        if a in i and b in i:
            num_a_b += 1
        if b in i:
            num_b += 1
    if num_a == 0:
        return (float(n)*num_a_b)/(num_b)
    elif num_b == 0:
        return (float(n)*num_a_b)/(num_a)
    else:
        return (float(n)*num_a_b)/(num_a*num_b)


df_lift_brand_aspiration =pd.DataFrame(columns=['brand','lift'])
i=0

for brand in brands:
    aspiration_lift=calc_lift_asp(str(brand),'aspiration', df7.comments_unique)
    df_lift_brand_aspiration.loc[i]=[ str(brand),aspiration_lift]
    i=i+1

df8 = df_lift_brand_aspiration.sort_values('lift',ascending = False).groupby('brand').head(10)
print(df8.sort_values(by = 'lift',ascending=False))
```

```
         brand      lift
25       volvo  1.691354
1         audi  1.546679
15    mercedes  1.508371
21      subaru  1.485712
2          bmw  1.470025
11    infiniti  1.412482
16     mercury  1.406017
0        acura  1.361428
24  volkswagen  1.350198
18      nissan  1.324240
14       mazda  1.321958
3        buick  1.312628
17  mitsubishi  1.304331
20      saturn  1.300789
10     hyundai  1.240963
5    chevrolet  1.238123
19     pontiac  1.202112
23      toyota  1.197691
9        honda  1.193855
12         kia  1.176710
8         ford  1.156197
6     chrysler  1.137441
4     cadillac  1.116586
22      suzuki  1.105420
7        dodge  1.081874
13     lincoln  0.958630
```